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THESIS

EXPLOITING NAVY OFFICER
END-OF-ACTIVE-OBLIGATED-SERVICE (EAOS)
DATE IN FORECASTING LOSSES

by

Michael C. Campbell

December 1987

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The thesis describes the generation and analysis of several simple loss rate forecasting models. The models are divided into two classes, those that incorporate eligibility data and those that do not.

Aviation officers, particularly pilots, were narrowed down to Lieutenants with four to nine years of commissioned service. They were divided into three communities (jet, prop, and helo).

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Exploiting Navy Officer End-of-Active-Obligated-Service (EAOS) Date In Forecasting Losses

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I. INTRODUCTION

A. PROBLEM

The key to effective military personnel planning is accurate loss forecasting. Accurate estimates of future losses enable personnel managers to determine the number of individuals to recruit and promote, as well as the size and cost of future personnel inventories. Officer personnel losses can generally be grouped into two distinct types: voluntary and involuntary. The voluntary portion (e.g., resignations, most retirements) is the largest and most volatile. Time series and econometric methods are used currently to forecast voluntary loss rates. Both classes of methods focus on trends in *historical* loss rates (through data processing, all historical losses are partitioned into either voluntary or involuntary groups). The present modelling techniques incorporate little or no information about the ability of a current or future population of officers to make a voluntary decision to stay or leave the Navy. Put differently, the techniques do not consider the portion of a begin-year inventory that is at risk or eligible to leave.

The Navy Personnel Research and Development Center (NPRDC) has developed Navy officer End-of-Active-Obligated Service (EAOS) dates for all officers on active duty at the end of FYs 1974-87. These data determine who is eligible to leave the Navy immediately (no obligation), who will be free of obligation sometime in the upcoming fiscal year (less than one year remaining on contract), and who will be ineligible to leave during the fiscal year (greater than one year remaining on contract). When aggregated, the first two groups comprise the population at risk for making voluntary loss decisions. To date, these data have *not* been exploited in any of the loss forecasting techniques. It is felt that this information can contribute to improved forecast accuracy of existing methods, especially by anticipating turning points in loss behavior. This thesis examines quantitatively the usefulness of these eligibility data to accurate officer loss forecasting.

B. OBJECTIVE

The thesis describes the generation and analysis of several simple loss rate forecasting models. The models are divided into two classes, those that incorporate eligibility data and those that do not. The study compares the forecast accuracy of these methods over a five year historical period (FY1982-1986). The validation results are presented in several ways and analyzed to determine if the eligibility data contributes to improved loss forecasting.

C. PREVIOUS STUDIES

In a 1978 report, Edward Bres and Murray Rowe, analysts from NPRDC, describe a study to improve existing Unrestricted Line (URL) loss rate forecasting methods. [Ref. 1]

A number of standard extrapolation techniques (e.g., averaging, exponential smoothing, time series) were tested to forecast loss rates for the total URL. These techniques used historical loss rate data (FY 1969-1977) arrayed by paygrade, years of commissioned service (YCS)[1], and promotion status. Estimates were compared to find the *most accurate* forecasting technique, based on their relative predictive accuracy over time.

A technique was judged superior to another if it had a lower mean absolute error (MAE). The analysis showed that an Autoregressive Time Series-Minimum Absolute Deviation (MAD--3 years) technique had the minimum MAE in 68 percent grade/YCS cells. Alternatively, the method used by OP-01 at the time, Weighted Moving Average (7 years), produced the best results in only 10.7 percent of the cells.

In October of 1980, Bres and Rowe conducted another study which would improve the measure of Navy officer retention [Ref. 2]. Currently used by offices of the Deputy Chief of Naval Operations (Manpower, Personnel, and Training) (OP-01) was the retention rate (RR). The RR was used to assess the Navy's ability to build and maintain a career force of officers. This rate employed the minimum service requirement (MSR) as a point of reference[2]. However, since the MSR frequently did not reflect an officer's true obligation, the RR tended to be overstated. In turn, the maintainability of the career force was overstated.

[1]Years of commissioned service are computed from an officer's relative year group. This year group is the fiscal year of first commissioning. An officer's relative year group is then the number of years between the current fiscal year and that first commissioning. Hence, relative year group serves as a measure of length of (commissioned) service.

[2]Minimum service requirement (MSR) is the obligated service an officer incurs as a result of initial commissioning and specialized warfare training. The MSR differs by commissioning source (e.g., a Naval Academy graduate receives a longer MSR than an Officer Candidate School graduate.) and by warfare training. (e.g., the service obligation for flight training exceeds that for Surface Warfare Officers' School).

The Base Force Retention Rate (BFR) was intended to replace the outdated RR. The BFR did not rely on MSR-based computations. It was simply the proportion of the career force base (CFB) (officers between 5 and 10 years of commissioned service) who resign their commissions annually[3].

Bres and Rowe found that the BFR was most useful for identifying changes or trends in the overall retention behavior of a community's CFB--trends that the conventional RR might not reveal at all or might uncover much later than would the BFR.

To properly address the feasibility of future officer manpower needs required the simultaneous consideration of manpower requirements, the existing and projected personnel inventory, and the projected supply of new officers. All of these management functions are interrelated, but they are organizationally distinct and lack the coherent linkages necessary to respond adequately and rapidly to planning and programming questions. To come closer to the way the officer manpower system really works and to improve response time, officer manpower management must function dynamically using a common set of models and policies.

In 1981, NPRDC deployed the initial version of the Structured Accession Planning System for Officers (STRAP-O)[4]. [Ref. 3] STRAP-O assesses the feasibility of achieving Navy officer manpower plans. Two models form the core of the STRAP-O system: the Navy Officer Force Projection (OPRO) model [Ref. 4]. and the Officer Retention Forecasting model (ORFM) [Ref. 5].

OPRO uses predictions of personnel flow rates to project a begin year inventory into the future (by year). A starting inventory is successively projected (by year) into the future. This allows a manager to assess the feasibility of manpower goals, test the sensitivity of the force to policy changes, and develop promotion and accession plans.

The officer retention forecasting model (ORFM) is an integrated set of time-series and econometric models that produce loss rate forecasts for STRAP-O. Loss rate forecasts are generated over a seven-year horizon. The manager has the capability to alter these forecasts through a change in the real value of military pay or through the selection of the forecasting technique.

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[3]The complement of the BFR, 1-BFR, is that portion of the CFB who resign their commissions annually.

[4]A similar system for Navy enlisted personnel, the Structured Accession Planning System--Enlisted (STRAP-E), is also operational (see Silverman, 1979).

STRAP-O begins by estimating loss rates using ORFM, and then applying them to current inventories in OPRO. Some accession and promotion policies are specified along with pay grade end strength targets. OPRO then generates inventories and continuation rates describing officer personnel flow behavior under these policy specifications.

An initial Unrestricted Line (URL) version of STRAP-O was installed in the Deputy Chief of Naval Operations (OP-130) in September 1981. A total officer force version became operational in March 1982.

In August of 1986, NPRDC concluded a verification/validation study. FY1985 loss rates, gains, and promotion policies were used to project FY85 end strength by community, grade, and years of service (YOS).

NPRDC's general conclusions were:

1. The one-year validation of losses showed that no one methodology excelled. All four methodologies (Naive, Weighted, ACOL[5], and MAD[6]) underestimated losses for FY85.
2. The two error measures for losses, Weighted Absolute Error (WAE) and Weighted Mean Square Error (WMSE), gave nearly identical rankings of loss forecasting capabilities.
3. The one-year validation of inventories for FY85 showed that no one methodology excelled. Error rates tended to be less than five percent.

Improving inputs to the forecasting models requires accurate estimates of expected losses. Carol Mullins, from NPRDC, conducted a study in March of 1986. Her study was the Development of a Navy Officer End-of-Active-Obligated-Service (EAOS) Date[7].

At present, the minimum service requirement (MSR) date is the only measure of service obligation available on an officer's computerized personnel record. However, the MSR includes only obligation incurred by source of entry (e.g. Naval Academy) and primary warfare training (e.g., basic flight training). Obligations incurred after the

[5]ACOL is defined as the present value of the monetary returns from remaining in the Navy for one more period and then making the optimal stay or leave decision, minus the present value of the monetary returns from leaving the Navy immediately.

[6]MAD is defined as a technique that minimizes the sum of the absolute values of the errors between historical loss rates and loss rate estimates.

[7]The EAOS date will depend on whether the additional obligation was consecutive or concurrent. In a special version of the concurrent case, the additional obligation is exhausted prior to completion of the MSR. Then the EAOS date is simply the MSR.

expiration of the MSR do not appear on the personnel record. Because use of the MSR alone can lead to an inaccurate measurement of eligibility (Bres & Rowe, 1983), a more comprehensive measure is needed to capture all obligations. The study is a separation of officer personnel into those eligible to leave the Navy and those still under a service obligation. [Ref. 6: Mullins, 1986, page 1]

The two-stage algorithm extracts any data elements from officer master file records that may indicate that an obligation has been incurred. The EAOS date is computed in the second stage. The algorithm accounts for changing obligations and types across time, as well as newly implemented obligation programs.

ACOL and MAD techniques are primarily used in the STRAP-O forecasting model. With the advent of EAOS and defining eligible officers more accurately, we could conceivably generate a more accurate loss forecast. This would be incorporated in both ACOL and MAD models.

Because the present forecasting technique combines voluntary and involuntary losses together without regard to who is actually eligible to make a decision, I believe that this is a major flaw. If one knows who is eligible to make a decision his forecast for the future will become more accurate. Utilizing EAOS data will allow us to improve the forecast and I will attempt to prove this theory.

The next chapter will explain the methodology of the target population, data collected and variables used. In chapter three the analytical materials are applied to the equations. Chapter Four will define the results from our loss equations and prove which equation is actually better. Conclusions for manpower losses are offered in the final chapter.

II. METHODOLOGY

In this section, the data used to analyze the forecasting value of eligibility data are described.

The initial investigation was limited to active duty, unrestricted line, pilots from the grade of Ensign (O-1) through Lieutenant Commander (O-4). The management of non-active duty officers (non-active duty reservists and retirees) is sufficiently different to be excluded from this study. Restricted officers (limited duty officers (LDOs)) have a unique career path and service characteristics, and were not addressed in this analysis.

A. DATA COLLECTED

The data used in this thesis were derived from the Officer Personnel Information System (OPIS) and NPRDC's officer data processing system, FAIM-O. OPIS is an interactive information delivery system. Using data retrieval and display software, as well as data organization techniques, the system provides rapid access to a substantial amount of historical officer personnel information. OPIS is currently housed on an IBM 4381 mainframe computer at NPRDC, San Diego. Communication to NPRDC was via telephone line. The Officer Personnel Information System (OPIS) is organized hierarchically as illustrated in Figure 2.1 .

The OPIS database consists of officer personnel inventories and flows (e.g., losses, promotions) by designator, grade, YOS, sex, ethnic group, source of entry, and time remaining on obligation during the period FY75-87. All data except MSR-based retention, are produced by the FAIM-O database. FAIM-O is a longitudinal database built and maintained by NPRDC for OP-130. MSR-based retention data were provided by OP-136D. [Ref. 7]

B. DESCRIPTION OF DATA

Historical inventory and loss data were collected from OPIS for FY75 through FY86. Each inventory or loss variable was arrayed by pilot community (e.g., jet, prop, helo), paygrade, and years of completed service.

Navy pilots are trained and managed in three distinct communities: jet, propellor ("prop"), and helicopter ("helo"). The communitites are also distinguished by their career retention behavior (as the chart shows). While I originally looked at officers in

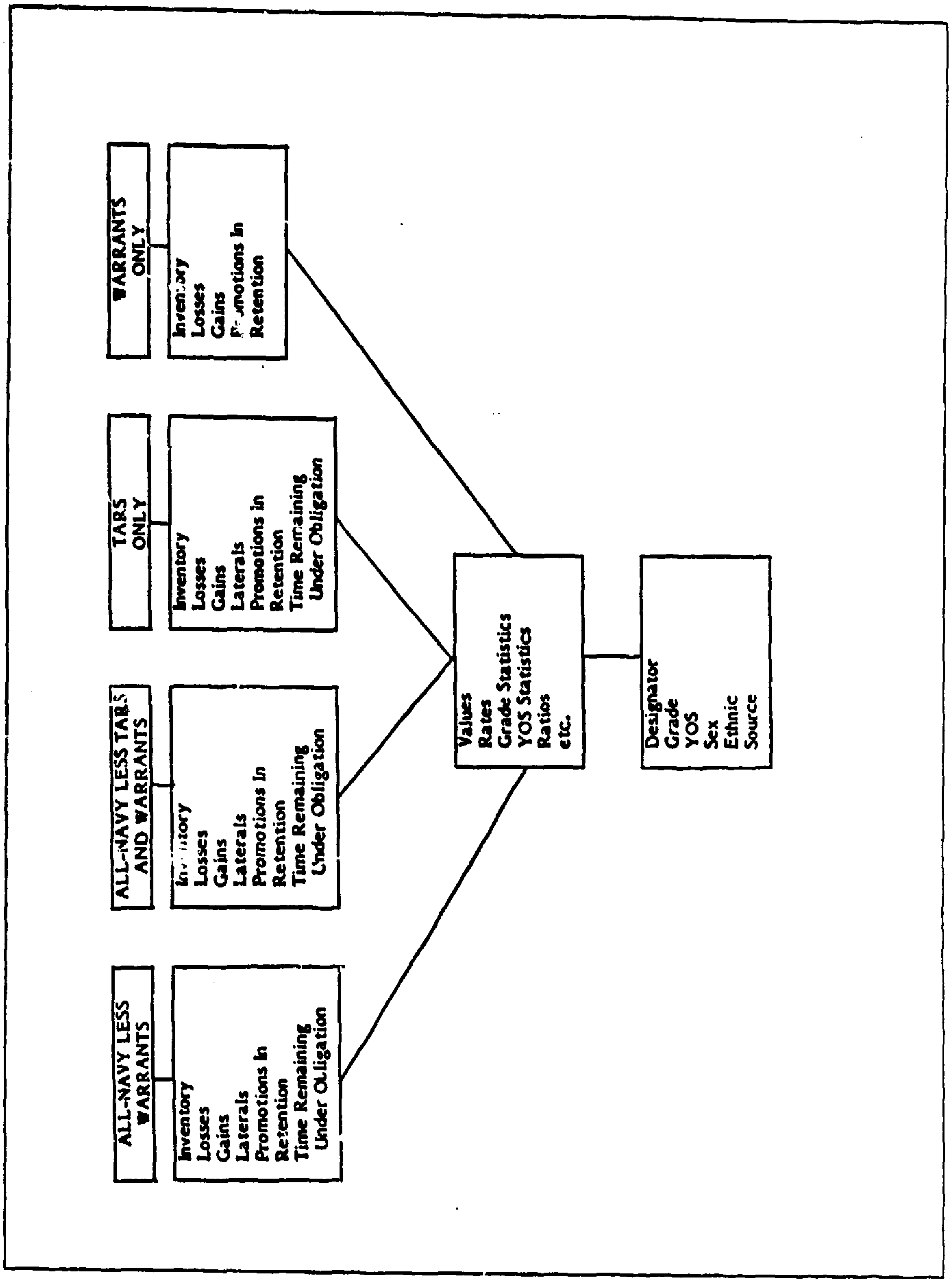

Figure 2.1 OPIS Hierarchy.

paygrades O-1 to O-4, I focused on O-3's. They represent paygrade from which most officers leave the Navy and where loss rates are most volatile and therefore difficult to predict. Finally, years of completed service (YCS) dimension is measured by subtracting an officer's year group from the fiscal year in which the officer is serving.

The following inventory and loss variables were used in the study.

1. **Inventory**

   The on-board count of pilots at the beginning of a fiscal year.

2. **Eligibles**

   The eligibles category represents the number of pilots with between zero and less than one year of service remaining on their contract at the beginning of a fiscal year. This group is frequently referred to as the "population at risk". The "eligibility rate" represents that portion of an inventory that is eligible to make a stay/leave decision.

3. **Voluntary Losses**

   The voluntary losses category accounts for the number of officers, who were eligible to stay or leave, made a voluntary decision to leave. For example, a voluntary loss occurs when an officer resigns or retires.

4. **Involuntary-Eligible Losses**

   The involuntary-eligible losses category includes individuals who, while eligible to make a stay or leave decision, were separated from the service involuntarily. Involuntary losses occur through death, discharge, or, in the case of reservists, release from active duty.

5. **Ineligibles**

   The ineligibles are the complement of eligibles or the difference between the inventory of pilots and the eligible population. The ineligibles category represents pilots who had more than one year of service remaining on their obligations.

6. **Involuntary-Ineligible Losses**

   The involuntary-ineligible category losses represents ineligible individuals.

III. ANALYSIS OF DATA

A. CURRENT METHODOLOGY

None of the existing loss forecasting methods used by the Navy incorporate knowledge of the size or composition of the current or expected population at risk. Instead, losses are forecasted from a begin-year inventory by first forecasting voluntary losses from the inventory, then forecasting involuntary losses from the *same* population, and finally summing the two forecasts. The equation is:

(1) TOTAL LOSSES/INV = VOL LOSSES/INV + INVOL LOSSES/INV

where:

INV	= Begin Fiscal Year Inventory
VOL LOSSES	= Voluntary Losses (e.g., resignations)
INVOL LOSSES	= Involuntary Losses (e.g., discharge, death)

Viewed another way:

Begin Fiscal Year Inventory		
Continue	Losses	
	Voluntary	Involuntary

This approach assumes implicitly that any member of the begin-inventory can voluntarily leave the Navy. The prediction of voluntary losses is not based on knowledge of the number of officers that can actually leave voluntarily. Conceivably, the Navy could predict more voluntary losses from a begin inventory than there are officers eligible to leave from the inventory. Stated differently, because the inventory is not separated into eligibles and ineligibles, analysis of policies that impact eligibles *only* (e.g., continuation bonuses) is difficult.

B. NEW METHODOLOGY

The development of a Navy officer EAOS date (Mullins, 1986) provided the first opportunity to incorporate eligibility data into Navy officer loss forecasting. The revised loss forecasting equation becomes:

(2) TOTAL LOSSES/INV = a{VOL LOSSES/ELIG + INVOL LOSSES/ELIG} + b{INVOL/INELIG}

where:

INV	= Begin Fiscal Year Inventory
VOL LOSSES	= Voluntary Losses
INVOL LOSSES	= Involuntary Losses
ELIG	= Number of Eligibles in Inventory
INELIG	= Number of Ineligibles in Inventory
a	= fraction of Inventory in forecast year that is eligible
b	= (1-a), fraction of inventory in forecast year that is ineligible

Incorporating the eligibility data provides a different conceptual view:

<table>
<tr><td colspan="5">Begin Fiscal Year Inventory</td></tr>
<tr><td colspan="3">Eligibles
("Population at Risk")</td><td colspan="2">Ineligibles</td></tr>
<tr><td>Continue</td><td colspan="2">Loss</td><td>Continue</td><td>Loss</td></tr>
<tr><td></td><td>Vol</td><td>Invol</td><td></td><td>Invol</td></tr>
</table>

In addition to more accurately identifying those portions of a begin-inventory capable of becoming various types of losses, the new method also has the advantage of using knowledge of the forecast year not available to the current method. Specifically, the new method uses the eligible and ineligible fractions for the first forecast year. For that year only, the rates are known with reasonable certainty. By weighting each of the sub-forecasts by their respective eligibility fractions, the new method exploits its knowledge of historical loss behavior but, tempers it with its knowledge of the future. This contrasts to the current method which depends solely on historical data to generate its forecasts.

Figure 3.1, suggests that knowledge of eligibility might be important to loss forecasting. The eligibility fraction not only differs among jet, prop, and helo pilots, but has changed dramatically over the last 12 years. The sharp increase in eligibility in the early 80's is due largely to the introduction of the Aviation Officer Continuation Pay or "pilot bonus".

C. METHODS OF FORECASTING

Since the primary purpose of this study was to determine the impact of eligibility data or loss forecasting, the study used simple rate forecasting methods to generate the sub-forecasts in equations (1) and (2). (In practice, the Navy employs more sophisticated methods of producing the sub-forecasts.) Three simple extrapolation methods were chosen.

1. Naive (PY)

This technique suggests that next year's loss rate will be the same as the current year's rate. Mathematically, it is stated as:

$$\hat{X}_{t+1} = X_t$$

where X_t is the loss rate for year t, and $\hat{X}_{t+1}$ is the estimated loss rate for year $t+1$ Generally, the naive model is accurate only if the data displays a constant trend.

2. Simple (Unweighted) Moving Averages (SM)

This approach takes a simple or unweighted moving average of historical loss rates to produce a forecast. I elected to use a three-year moving average. The equation is:

$$\hat{X}_{t+1} = \sum_{i=1}^{3} \frac{X_{t-i+1}}{3}$$

3. Weighted Moving Average (WM)

If trends in loss behavior suggest that the forecast should resemble the recent past more than the distant past, then a weighted moving average should be used. The WM method uses three years of historical data, but uses a 3-2-1 descending weighting scheme. The equation is:

$$\hat{X}_{t+1} = \sum_{i=1}^{3} \frac{X_{t-i+1} * (3-i+1)}{6}$$

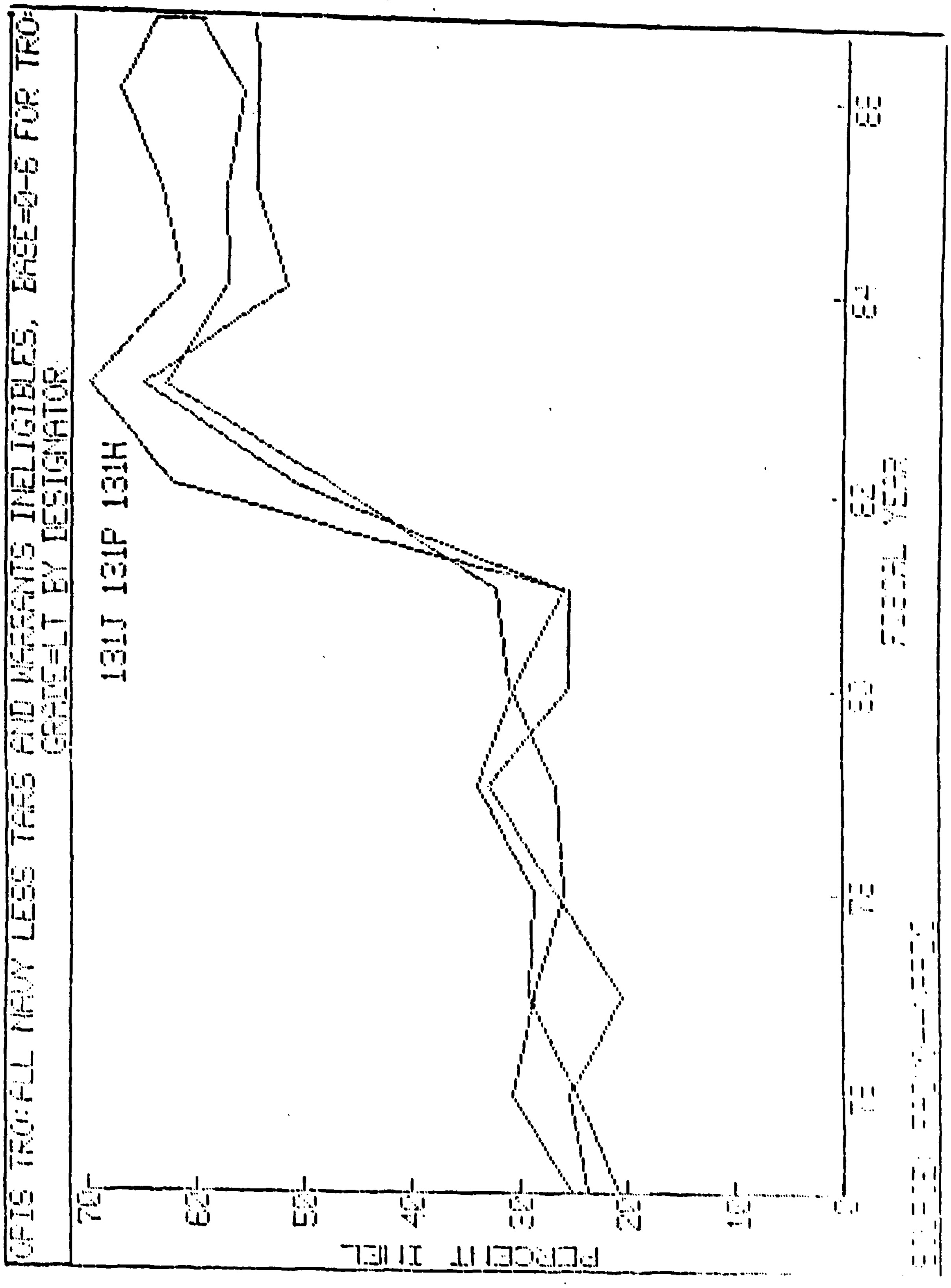

Figure 3.1 Loss Eligibility.

IV. RESULTS

A. PREDICTED VERSUS ACTUAL ANALYSIS

By comparing predicted loss rates to actual loss rates in Tables 1 , 2, and 3, the first conclusion that can be drawn is that EAOS forecasts contribute more to loss accuracy than does the BI results.

From the 90 cases analyzed, (13 cases were discarded because of "ties"; seventy-seven cases with unambiguous results remained). EAOS predicted 46 cases more accurately than BI. BI methods were more accurate in 31 cases. For example, FY1982, YCS 5, jet community, the actual loss rate for that year was 17 percent or 49 individuals. The best predictor for that time period was EAOS previous year (PY) with a 19.2 percent loss rate or 55 pilots. Six more pilots were predicted to leave than actually left, but five less than the best case for the BI technique. Overall, EAOS under-predicted slightly more often than it over-predicted. EAOS had 24 under-predictions (52 percent), 19 over-predictions (41 percent), and three cases where actual equal predicted (7 percent). In contrast, BI methods over-predicted more often. BI had 19 over (61 percent), 11 under (36 percent), and one equal to the actual (3 percent).

B. WEIGHTED AVERAGE ERROR OVER TIME

Table 4, summarizes the validity of the various methods over time (FY82-86), but displaying weighted average errors. Each year's forecast error is weighted by its begin-inventory. The table is separated into YCS and aviation community. Fiscal years 82-86 are again represented.

The smallest weighted error suggest the most accurate technique over the fiscal year validation period. For example, YCS 4, jet community the smallest error is .004 under the EAOS WM column. In YCS five, jet community the smallest error is .029 under the EAOS PY column and so on.

In the jet community four years out of six (67 percent), BI was a better predictor. EAOS predicted better in the prop and helo communities with four out of six YCS cells (67 percent). Seven out of eighteen best forecasting cases resulted in a weighted error of .05 or higher, four were BI and three EAOS. EAOS dominated in all communities for YCS 4 and 5. Results in YCS 7 to 9 were mixed.

TABLE I
PREDICTED VERSUS ACTUAL LOSS RATES

FISCAL YEAR	YCS	COMMUNITY	ACT. LOSS	ACT. INV.	ACT. LR	BI PY	BI WM	BI SM	EAOS PY	EAOS WM	EAOS SM
1982	4	JET	18	321	5.6%	4.0%	5.3%	5.5%	4.6%	5.9%	6.2%
1982	5	JET	49	288	17.0%	21.0%	24.2%	25.7%	19.2%	22.2%	23.6%
1982	6	JET	40	212	18.9%	20.0%	23.0%	25.0%	15.6%	18.5%	20.1%
1982	7	JET	13	125	10.4%	10.0%	17.5%	21.3%	5.2%	10.2%	12.3%
1982	8	JET	13	123	10.6%	8.0%	11.8%	14.0%	2.8%	4.4%	5.3%
1982	9	JET	4	23	17.4%	25.0%	21.8%	22.3%	12.0%	12.5%	13.1%
1983	4	JET	6	299	2.0%	5.0%	5.0%	5.3%	1.3%	1.5%	1.8%
1983	5	JET	36	327	11.0%	17.0%	19.8%	21.3%	14.7%	16.5%	17.5%
1983	6	JET	46	242	19.0%	[illegible]	19.5%	20.3%	14.0%	12.9%	12.8%
1983	7	JET	26	178	14.6%	11.0%	12.3%	14.0%	6.4%	6.0%	6.7%
1983	8	JET	8	122	6.6%	10.0%	9.8%	10.3%	6.0%	4.0%	3.5%
1983	9	JET	1	11	9.1%	17.0%	19.2%	18.7%	3.2%	3.8%	4.7%
1984	4	JET	4	275	1.5%	2.0%	3.3%	3.7%	1.0%	[illegible]	0.5%
1984	5	JET	26	319	8.2%	12.0%	15.2%	16.7%	8.5%	9.8%	10.6%
1984	6	JET	44	291	15.1%	19.0%	18.8%	19.0%	32.8%	26.8%	24.5%
1984	7	JET	26	207	12.6%	14.0%	12.3%	11.7%	24.5%	16.8%	13.6%
1984	8	JET	12	153	7.8%	7.0%	8.2%	8.3%	8.4%	7.1%	6.0%
1984	9	JET	1	9	11.1%	9.0%	14.3%	17.0%	22.0%	14.6%	11.8%
1985	4	JET	1	178	0.6%	1.0%	2.0%	2.7%	1.0%	0.8%	0.7%
1985	5	JET	25	280	8.9%	8.0%	10.8%	12.3%	[illegible]	8.6%	8.9%
1985	6	JET	99	292	33.9%	15.0%	16.8%	17.3%	14.2%	20.9%	22.0%
1985	7	JET	61	251	24.3%	12.0%	12.5%	12.3%	10.8%	13.8%	13.5%
1985	8	JET	21	179	11.7%	8.0%	8.0%	8.3%	10.4%	10.8%	10.8%
1985	9	JET	16	59	27.1%	11.0%	11.3%	12.3%	11.6%	12.5%	11.6%
1986	4	JET	2	289	0.7%	1.0%	1.2%	1.3%	1.0%	1.0%	1.0%
1986	5	JET	8	180	4.4%	9.0%	9.2%	9.7%	14.9%	14.2%	14.0%
1986	6	JET	60	248	24.2%	34.0%	25.2%	22.7%	35.4%	28.1%	27.6%
1986	7	JET	44	185	23.8%	25.0%	18.8%	17.0%	28.8%	22.6%	21.8%
1986	8	JET	15	189	7.9%	12.0%	9.8%	9.0%	10.8%	10.2%	10.0%
1986	9	JET	8	37	21.6%	27.0%	18.7%	15.7%	43.2%	29.5%	27.7%
1982	4	PROP	16	282	5.7%	5.0%	10.0%	11.0%	3.1%	5.5%	6.2%
1982	5	PROP	53	225	23.6%	27.0%	27.0%	28.0%	25.2%	26.6%	28.0%
1982	6	PROP	41	205	20.0%	23.0%	27.2%	29.7%	15.9%	20.0%	22.0%
1982	7	PROP	22	167	13.2%	12.0%	14.3%	16.0%	6.6%	8.1%	9.1%
1982	8	PROP	8	96	8.3%	11.0%	12.5%	13.3%	4.1%	4.7%	5.0%
1982	9	PROP	1	16	6.3%	26.0%	26.3%	28.0%	6.8%	9.2%	9.4%
1983	4	PROP	0	247	0.0%	6.0%	7.5%	9.3%	1.0%	0.9%	1.0%
1983	5	PROP	34	294	11.6%	23.0%	24.5%	24.7%	20.4%	21.2%	21.4%
1983	6	PROP	19	175	10.9%	20.0%	22.3%	23.7%	14.9%	14.1%	[illegible]
1983	7	PROP	12	166	7.2%	13.0%	12.8%	13.0%	7.2%	5.6%	5.1%
1983	8	PROP	9	160	5.6%	8.0%	9.8%	10.7%	4.6%	3.4%	3.1%
1983	9	PROP	4	21	19.0%	6.0%	15.3%	18.0%	4.6%	6.0%	7.3%
1984	4	PROP	5	223	2.2%	0.0%	2.8%	3.7%	0.0%	0.0%	0.0%
1984	5	PROP	24	265	9.1%	11.0%	17.7%	20.3%	12.2%	17.0%	18.7%
1984	6	PROP	53	258	20.5%	11.0%	16.0%	18.0%	21.3%	23.7%	23.8%
1984	7	PROP	28	170	16.5%	7.0%	9.8%	10.7%	12.8%	11.9%	10.3%
1984	8	PROP	5	157	3.2%	5.0%	7.0%	8.0%	7.1%	5.8%	5.1%
1984	9	PROP	13	31	41.9%	19.0%	15.8%	17.0%	30.4%	19.6%	16.1%

TABLE 2

PREDICTED VERSUS ACTUAL LOSS RATES (CONT.)

FISCAL YEAR	YCS	COMMUNITY	ACT. LOSS	ACT. INV.	ACT. LR	BI PY	BI WM	BI SM	EAOS FY	EAOS WM	EAOS SM
1985	4	PROP	3	192	1.6%	2.0%	2.0%	2.7%	1.0%	0.5%	0.3%
1985	5	PROP	46	223	20.6%	3.0%	12.0%	14.3%	9.2%	12.3%	14.4%
1985	6	PROP	95	237	40.1%	20.0%	17.0%	17.0%	17.5%	18.9%	20.0%
1985	7	PROP	52	201	25.9%	17.0%	13.0%	12.3%	14.7%	13.0%	12.6%
1985	8	PROP	15	137	10.9%	3.0%	4.5%	5.3%	4.3%	6.3%	6.8%
1985	9	PROP	25	67	37.3%	42.0%	28.3%	22.3%	42.0%	32.2%	26.6%
1986	4	PROP	6	232	2.1%	2.0%	1.7%	1.3%	2.0%	1.3%	1.0%
1986	5	PROP	49	200	24.5%	20.0%	14.8%	13.3%	22.1%	16.5%	15.0%
1986	6	PROP	72	170	42.4%	40.0%	28.5%	23.7%	49.0%	35.3%	30.9%
1986	7	PROP	25	139	18.7%	26.0%	19.8%	16.7%	33.0%	25.1%	22.0%
1986	8	PROP	15	145	10.3%	11.0%	7.3%	6.3%	11.3%	8.7%	8.4%
1986	9	PROP	7	30	23.3%	37.0%	35.7%	32.7%	69.0%	61.4%	59.8%
1982	4	HELO	3	138	2.2%	1.0%	1.3%	1.7%	3.0%	2.2%	2.2%
1982	5	HELO	3	117	2.6%	6.0%	8.8%	10.0%	4.8%	6.9%	7.9%
1982	6	HELO	13	150	8.7%	13.0%	13.0%	12.7%	7.0%	7.0%	6.8%
1982	7	HELO	8	169	4.7%	6.0%	7.0%	7.3%	2.8%	3.5%	3.5%
1982	8	HELO	1	101	1.0%	11.0%	8.7%	8.0%	6.5%	5.5%	4.8%
1982	9	HELO	3	25	12.0%	28.0%	22.7%	19.7%	19.4%	15.2%	12.9%
1983	4	HELO	2	164	1.2%	2.0%	1.5%	1.3%	1.4%	1.7%	1.5%
1983	5	HELO	8	181	4.4%	3.0%	5.3%	6.7%	2.4%	3.7%	4.5%
1983	6	HELO	13	122	10.7%	9.0%	11.2%	12.0%	11.6%	10.3%	10.1%
1983	7	HELO	3	136	2.2%	5.0%	5.8%	6.3%	2.4%	2.6%	3.0%
1983	8	HELO	9	153	5.9%	1.0%	5.2%	6.0%	0.5%	2.9%	3.7%
1983	9	HELO	5	11	45.5%	12.0%	18.8%	20.3%	8.1%	11.5%	12.1%
1984	4	HELO	2	191	1.0%	1.0%	1.3%	1.3%	1.0%	1.3%	1.7%
1984	5	HELO	9	172	5.2%	4.0%	4.0%	4.3%	4.8%	3.9%	3.8%
1984	6	HELO	13	175	7.4%	10.0%	10.2%	10.7%	14.4%	14.5%	14.0%
1984	7	HELO	11	111	9.9%	2.0%	3.7%	4.3%	6.8%	6.4%	5.9%
1984	8	HELO	4	134	3.0%	6.0%	5.2%	6.0%	5.9%	4.0%	3.9%
1984	9	HELO	8	14	57.1%	45.0%	31.2%	28.3%	38.2%	23.8%	20.0%
1985	4	HELO	0	125	0.0%	2.0%	1.7%	1.7%	1.0%	1.0%	1.0%
1985	5	HELO	5	186	2.7%	5.0%	4.3%	4.0%	6.1%	5.3%	4.8%
1985	6	HELO	13	163	8.0%	8.0%	8.8%	9.0%	6.7%	9.9%	11.2%
1985	7	HELO	22	156	14.1%	10.0%	6.5%	5.7%	5.3%	4.5%	4.2%
1985	8	HELO	5	97	5.2%	3.0%	3.7%	3.3%	3.8%	4.2%	3.7%
1985	9	HELO	8	44	18.2%	58.0%	46.0%	38.3%	39.5%	29.1%	22.0%
1986	4	HELO	0	236	0.0%	0.0%	0.8%	1.0%	0.0%	0.5%	0.7%
1986	5	HELO	7	165	4.2%	3.0%	3.8%	4.0%	2.5%	3.9%	4.3%
1986	6	HELO	23	174	13.2%	8.0%	8.3%	8.7%	8.4%	8.8%	9.6%
1986	7	HELO	19	149	12.8%	14.0%	10.7%	8.7%	22.4%	14.9%	12.2%
1986	8	HELO	11	134	8.2%	5.0%	4.5%	4.7%	5.3%	5.3%	5.5%
1986	9	HELO	10	47	21.3%	19.0%	36.3%	40.7%	30.7%	41.8%	43.4%

TABLE 3
PREDICTED VERSUS ACTUAL LOSS RATES SUMMARY

JET	82	83	84	85	86	BI	EAOS
4	BI	EAOS	BI/EAOS	EAOS	BI/EAOS	3	4
5	EAOS	EAOS	EAOS	EAOS	BI	1	4
6	EAOS	BI	BI	EAOS	BI	3	2
7	EAOS	BI	BI	EAOS	BI/EAOS	3	3
8	BI	EAOS	BI	EAOS	BI	3	2
9	EAOS	EAOS	EAOS	EAOS	BI	1	4

PROP	82	83	84	85	86	BI	EAOS
4	EAOS	EAOS	BI	BI	BI/EAOS	3	3
5	EAOS	EAOS	BI	EAOS	EAOS	1	4
6	EAOS	EAOS	EAOS	BI/EAOS	BI	2	4
7	BI	EAOS	EAOS	BI	BI	3	2
8	BI	EAOS	BI	EAOS	BI	3	2
9	EAOS	BI	EAOS	BI/EAOS	BI	3	3

HELO	82	83	84	85	86	BI	EAOS
4	EAOS	BI	BI/EAOS	EAOS	BI/EAOS	3	4
5	EAOS	EAOS	EAOS	BI	EAOS	1	4
6	EAOS	EAOS	BI	BI	EAOS	2	3
7	EAOS	EAOS	EAOS	BI	EAOS	1	4
8	EAOS	BI	EAOS	EAOS	EAOS	1	4
9	EAOS	BI	BI	EAOS	BI	3	2

TABLE 4
WEIGHTED AVERAGE ERROR

FISCAL YEAR	YCS	COMMUNITY	BI PY	BI WM	BI SM	EAOS PY	EAOS WM	EAOS SM
82-86	4	JET	0.013	0.014	0.016	0.006	0.004	0.005
	5	JET	0.039	0.061	0.075	0.029	0.041	0.047
	6	JET	0.074	0.057	0.062	0.121	0.076	0.068
	7	JET	0.045	0.055	0.063	0.094	0.056	0.052
	8	JET	0.030	0.021	0.023	0.025	0.023	0.024
	9	JET	0.103	0.092	0.098	0.144	0.098	0.093
82-86	4	PROP	0.018	0.028	0.037	0.013	0.010	0.011
	5	PROP	0.067	0.089	0.095	0.056	0.075	0.081
	6	PROP	0.094	0.119	0.129	0.078	0.073	0.082
	7	PROP	0.066	0.053	0.064	0.071	0.064	0.061
	8	PROP	0.030	0.043	0.049	0.032	0.029	0.027
	9	PROP	0.123	0.132	0.147	0.143	0.151	0.176
82-86	4	HELO	0.006	0.008	0.007	0.003	0.005	0.006
	5	HELO	0.018	0.018	0.021	0.020	0.017	0.016
	6	HELO	0.028	0.028	0.029	0.034	0.033	0.034
	7	HELO	0.032	0.043	0.049	0.049	0.034	0.033
	8	HELO	0.045	0.029	0.029	0.037	0.025	0.022
	9	HELO	0.138	0.202	0.189	0.153	0.165	0.150

TABLE 5

TURNING POINT ANALYSIS

PROP FY	5 YOS BEST	ACT LOSS	PRED	DEV	ALT BEST	PRED	DEV
81-82	EAOS PY	23.6	25.6	+2.0	BI PY	27.0	+3.4
83-84	BI PY	9.1	11.0	+1.9	EAOS PY	12.2	+3.1

HELO FY	5 YOS BEST	ACT LOSS	PRED	DEV	ALT BEST	PRED	DEV
81-82	EAOS PY	2.6	4.8	+2.2	BI PY	6.0	+3.4
82-83	EAOS SM	4.4	4.5	+0.1	BI WM	5.3	+0.9

JET FY	6 YOS BEST	ACT LOSS	PRED	DEV	ALT BEST	PRED	DEV
82-83	BI WM	19.0	19.5	+0.5	EAOS PY	14.0	-5.0
83-84	BI WM	15.1	18.8	+3.7	EAOS SM	24.5	+9.4
84-85	EAOS SM	33.9	22.0	-11.9	BI SM	17.3	-16.6

PROP FY	6 YOS BEST	ACT LOSS	PRED	DEV	ALT BEST	PRED	DEV
83-84	EAOS PY	20.5	21.3	+0.8	BI SM	18.0	-2.5
84-85	EAOS SM	40.1	20.0	-20.1	BI PY	20.0	-20.1

JET FY	7 YOS BEST	ACT LOSS	PRED	DEV	ALT BEST	PRED	DEV
82-83	BI SM	14.6	14.0	-0.6	EAOS SM	6.7	-7.9
83-84	BI SM	12.6	12.3	-0.3	EAOS SM	13.6	+1.0
84-85	EAOS SM	24.3	13.5	-10.8	BI WM	12.5	-11.8

PROP FY	7 YOS BEST	ACT LOSS	PRED	DEV	ALT BEST	PRED	DEV
81-82	BI WM	13.2	14.3	+1.1	EAOS SM	9.1	-4.1
82-83	EAOS PY	7.2	7.2	0	BI WM	12.8	+5.6
84-85	BI PY	25.9	17.0	-8.9	EAOS PY	14.7	-11.2

HELO FY	7 YOS BEST	ACT LOSS	PRED	DEV	ALT BEST	PRED	DEV
84-85	BI PY	14.1	10.0	-4.1	EAOS PY	5.3	-8.8

JET FY	8 YOS BEST	ACT LOSS	PRED	DEV	ALT BEST	PRED	DEV
82-83	EAOS PY	6.6	6.0	-0.6	BI WM	9.8	+3.2
83-84	BI WM	7.8	8.2	+0.4	EAOS PY	8.4	+0.6
84-85	EAOS SM	11.7	10.8	-0.9	BI SM	8.3	-3.4

PROP FY	8 YOS BEST	ACT LOSS	PRED	DEV	ALT BEST	PRED	DEV
82-83	EAOS PY	5.6	4.6	-1.0	BI PY	8.0	+2.4
83-84	BI PY	3.2	5.0	+1.8	EAOS SM	5.1	+1.9
84-85	EAOS SM	10.9	6.8	-4.1	BI SM	5.3	-5.6

HELO FY	8 YOS BEST	ACT LOSS	PRED	DEV	ALT BEST	PRED	DEV
81-82	EAOS SM	1.0	4.8	+3.8	BI SM	8.0	+7.0
82-83	BI SM	5.9	6.0	+0.1	EAOS SM	3.7	-2.2
84-85	EAOS SM	5.2	4.2	-1.0	BI WM	3.7	-1.5

25 TURN POINTS		OVER	PREDICT UNDER	EVEN
EAOS	14	5	8	1
BI	11	7	4	0

C. TURNING-POINT ANALYSIS

With a stable flow of personnel, it is relatively easy to predict loss behavior. Most techniques should predict well under these conditions. However, strong techniques should also be able to predict changes in the direction of rates over time. Statistically, these shifts are known as "turning points".

The most significant turning points in the historical data are listed on Table 5 . The table lists the significant turning point year and which method was the better predictor. It then lists the actual loss rate, the best predicted rate, and the deviation under or over from the actual rate. The alternate (second best) predictor is listed along side with the same indicators as before. As an example, a prop pilot with YOS 5 had a significant turning point at FY81-82. In 1982 the best predictor was EAOS with a rate of 25.6 percent, the actual was 23.6 percent. The predicted value was 2.0 percent over the actual rate. The alternate would, of course, be BI with a predicted value of 27.0 percent and it over predicted by 3.4 percent.

Of the 25 major turning points selected the better predictor was EAOS with 14 (56 percent) and BI drew 11 (44 percent). There did not seem to be a major difference between the two methods. When tabulating the numbers it did show that EAOS under predicted more often, while BI over predicted more frequently.

V. CONCLUSIONS

This study suggests that by utilizing the EAOS date loss forecasting techniques can be more accurate. The following findings are germane:

1. Predicted versus actual loss rates showed that EAOS would perform better than the present system described by the BI method. EAOS predicted better 60 percent of the time.
2. Over a five year validation horizon, EAOS predicted better 56 percent of the time. BI was better in the jet community, but EAOS performed better in the prop and helo community.
3. Turning point analysis is another important criteria for evaluating loss rate forecasting techniques. EAOS again predicted 56 percent, whereas BI was 44 percent.

This analysis suggests that the EAOS data will be absorbed into the present forecasting techniques through MAD and ACOL models incorporated within STRAP-O.

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